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Residential peak electricity demand response—Highlights of some behavioural issues

Samuel Gyamfi [a,*], Susan Krumdieck [b,1], Tania Urmee [a]

[a] School of Engineering and Energy, Murdoch University, Murdoch, Western Australia 6150, Australia
[b] Department of Mechanical Engineering, University of Canterbury, Private Bag 4800, Christchurch, New Zealand

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ABSTRACT

Electricity demand response refers to consumer actions that change the utility load profile in a way that reduces costs or improves grid security. The focus of demand response has mainly been on the commercial and big industrial sectors because of the large demand reduction that they can offer to the utility grid operators. Utilities are showing increasing interest in residential demand response (RDR). RDR can be treated as an energy resource which can be assessed and commercially developed, however, there are still some issues that remain to be addressed for RDR to be successful. These include price unresponsiveness of some residential consumers, equity issues and high cost of the metering infrastructure. The aim of this paper is to investigate and present some of the challenges in achieving effective voluntary demand reduction based on a review of residential demand response literature as well as the general residential energy use behaviour literature. The authors propose the use of a hybrid engineering approach using social psychology and economic behaviour models to overcome these challenges and realize the benefits of supply security and cost management.

Contents

1. Introduction

Peak demand, the highest demand that has occurred on a utility network over a specified period of time, has become a major global issue. Critical peak demand typically occurs when there is co-incident high usage among all the end use sectors; residential, industrial and commercial. In a particular network, this may occur for only a few hours in a year [1]. For example, the load duration curve of South Australian power networks for 2011 shows that demand exceeded 2500 MW for approximately 0.7% of the time [2]. Critical peak demand poses a high risk of power system failure. The generation and distribution investments to maintain sufficient reserve margin have high marginal cost [3]. Peak load is usually

* Corresponding author. Tel.: +61 8 9360 7504; fax: +61 8 9360 6346.
E-mail address: s.gyamfi@murdoch.edu.au (S. Gyamfi).
[1] Tel.: +64 3364 2987x7249; fax: +64 3364 2078.

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supplied with fossil fuels and pumped storage hydropower plants, resulting in high emission factors and environmental impacts.

Demand response is an alternative to additional infrastructure to maintain the safe margin between generation and/or distribution capacity and demand. The broadest definition of demand response is the one given by the United State Department of Energy as: “Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized” [4]. Demand response programs are used to reduce demand peaks and fill load valleys, thus levelling out the load pattern to better match base load, improving the system load factor (i.e. the average load over peak load). Demand response can ultimately reduce the stresses on electricity networks.

Demand response is a particular type of traditional demand-side management (DSM) program. DSM programs enable utilities to manage electricity supply reliability and costs by influencing consumer demand patterns to optimally deploy generation assets [5]. DSM encompasses a broad set of actions on the part of consumers and utilities. DSM programs have promoted energy efficient appliances, conservation, co-generation and automation of industrial processes and space conditioning. DSM programs mainly rely on the electricity price signals and education campaigns [5].

The benefits of demand response include cost reduction, improved environmental sustainability (if it results in reduced fossil fuel use), increased supply reliability and market efficiency, customer service improvement and market power mitigation [6]. Demand response is increasingly recognized as essential to a well-functioning electricity market and it forms part of the “smart grid” concept [7]. Developments in information and communication technologies (ICT) could make a highly responsive system feasible.

Past experience of demand response has mainly been in the industrial and commercial sectors where significant demand reductions have been reported for some programs [8]. There has been a growing interest in residential demand response particularly due to the significant contribution of the residential sector to the system peak demand: more than 45% in the UK [9]; above 50% in New Zealand [10] and more than 50% in South Australia [11]. Positive results have been reported for residential DR programs in terms of reducing peak load[12,13]. In these programs, large residential loads like air conditioners or electric water heaters are controlled by the utilities using ripple controls.

Price response is a category of demand response that has garnered attention in recent times. While positive results have been reported for some price response programs, with the majority of them being on pilot bases [14], issues still remain. A significant proportion of residential customers are non-responsive to price [15], and higher prices discriminate against lower income households [16]. The cost of supporting infrastructure (smart meters, in-home-displays, etc) would be staggering[14]. The lack of quantitative understanding of consumer behaviour and end-use activity adaptive capacity is a significant barrier to design and deployment of effective DR programs [17]. For example, most smart appliances have automatic energy saving modes that can be set up by the customers so that they run only during off-peak hours [18], but it is still not clear how customers will embrace these ‘smart’ machine. For example, a study that monitored the operating modes of 35,471 installed programmable thermostats in households within the jurisdiction of four utilities in the USA (LIPA, ConEd, SCE, SDG&E) found only 47% in program mode in which the thermostat uses the schedule previously input by the occupant to control temperature set points. The rest were in Hold mode, which effectively turns the thermostat into a manual thermostat [19].

This paper reviews the potential, as well as economic and social issues, and concerns raised by demand response practitioners and researchers. The first part of the paper reviews social and behavioural factors in household end-use demand response. This is followed by a review of models that are employed for measuring consumer demand response as well as reviews of major demand response case studies, highlighting their success in terms of behaviour change and the demand reduction achieved. Key issues and concerns identified in the literature are also highlighted. The authors provide suggestions on how effective demand response programs could be achieved in the residential sector.

2. Variation in residential energy use—the significance of human behaviour

Households vary significantly in the amount of energy they use [20]. These variations could be attributed to differences in engineering and economic factors, energy type and household characteristics (family size, age of household members, race/ethnicity, etc.). However, when these factors are controlled or set, large variations in the amount of energy use in individual houses still remain. This was first revealed by a study at the Princeton Centre for Energy and Environmental Research (the Twin River Project, New Jersey) [20]. In that study, Socolow and his team showed that houses of similar sizes, occupied by demographically similar families, with a similar set of appliances and under the same geographical condition, varied in energy consumption by as much as 200%. When some houses were monitored for energy consumption after they have been retrofitted to the same standard, large variations in consumption still remained [20]. Finally, in the houses where the occupants had moved, the energy consumption of the new occupants could not be predicted from the previous families' levels of energy use [21].

Similarly, a recent study that measured the energy use in 10 identical all-electric homes, with the same set of appliances and equipment, found the energy use of the lowest to the highest consumers varied by as much as 260% [22]. A review of this type of research from the 1970s to the early 1990s conducted by Lutzenhiser, [23] concluded that “…the residential sector consumption seems to be characterized by variability and change, with human behaviour playing a central role in both the short term and long term initiation, maintenance and alteration of energy flow”. These results suggest that intervention strategies designed to promote sustainable energy consumption behaviours could result in significant energy savings.

Literature on human energy use behaviour can broadly be divided between economics, where demand is calculated using income and price elasticity, and social-psychological studies that collect information about attitudinal and behavioural attributes (habits, emotions, social norms, moral behaviours and cognitive limitations) that affect personal decisions to manage energy consumption more effectively [24]. Sections 2.1 and 2.2 review these two main disciplinary perspectives on residential energy consumption.

2.1. Economic model of behaviour

As a social science discipline, a major part of economics is concerned with the study of human behaviour. In economics, price and income are important determinants of energy consumption. From the income and price theories of demand, several useful predictions can be made about consumer behaviour. An Engel curve [25], for example, describes how the quantity demanded of a good or service changes as the consumer's income level changes. The ratio of percentage change in demand to the percentage

change in a consumer's income is referred to as Income Elasticity of Demand. Consumer behaviour has also been studied under price changes. A change in consumer demand that results from a unit change in price is commonly referred to as price elasticity of demand. The model of influencing consumer demand with price is based on the microeconomic theory of utility maximization and consumer rationality [26]. This theory is based on the notion that consumers weigh the expected costs and benefits of different actions and choose those actions which are most beneficial or least costly to them [27]. Demand-side management programs that promote conservation through energy pricing, development of new technologies and subsidies are based on this theory [5]. A very important part of DSM process involves consistent evaluation of demand-side to supply-side alternative to assess their cost-effectiveness.

The elasticity of electricity demand with respect to price change has been calculated in many residential sector electricity demand studies [14,15,28,29]. One measurement of elasticity is the customer change in demand in the same time period that the price change occurs, known as own price elasticity (commonly referred to as price elasticity). It is mathematically written as:

$$EP = \frac{\%\Delta Q}{\%\Delta P} \qquad 2.1$$

where EP is the own price elasticity, $\%\Delta Q$ represents demand change resulting from $\%\Delta P$ price change. The other measurement of load shifting behaviour is known as the elasticity of substitution. It is defined as the negative of the percentage change in the ratio of peak to off-peak demand, divided by the percentage change in the ratio of peak to off-peak price. Mathematically, it is written as:

$$EP_{subs} = \frac{-\%\Delta(Q_P/Q_O)}{\%\Delta(P_P/P_O)} \qquad 2.2$$

where, EP_{subs}, is price elasticity of substitution, calculated from the percent change in peak to off-peak price ratio, $\%\Delta\ (P_P/P_O)$, and the peak to off-peak demand ratio, $\%\Delta\ (Q_P/Q_O)$. When the necessary data is available, elasticity of substitution can be compared with own price elasticity [30]. In other words, load shifting studies can be compared to load reduction studies when the necessary data (appliance holdings, customer characteristics, and climate) are properly accounted for. Examples of these measurements are provided in Sections 3.1 and 3.2.

2.2. Socio-psychological model of behaviour

Experimental work conducted by psychologists shows that individuals do not make consistently rational decisions, as suggested by the economists [31]. Time inconsistency, reference dependence and bounded rationality are some of the examples cited in the literature as far as energy use is concerned [32]. In each of these cases, individual choices violate one or more of the axioms of preference on which utility theory is based. Stern for example argues that, not only is the information regarding residential energy use held by consumers incomplete, but systematically incorrect and that people tend to overestimate the amount of energy they use and what may be saved through application of energy efficiency technologies [33]. The economic theory of rational actors does not fully describe human behaviour; specifically, it does not adequately capture energy related behaviour in the residential sector. Psychologists have therefore been arguing that the economic models of "rational behaviour" should include the "cost" of the time, attention and effort required for adaptation to changing prices. In business decision-making these indirect costs are probably small when compared with the direct costs that depend on the decisions, but in household decision-making the indirect costs might be higher than the possible savings in the direct costs. The concept of bounded rationality by Simon, for instance, suggests that individuals employ heuristics to make decisions rather than a strictly rigid rule of optimization [34]. They do so because of the complexity of the situations, and their inability to process and compute the expected utility of every alternative action.

There has been a small group of researchers who have demonstrated the importance of looking at the residential energy in the social context. They argue that though promoting changes in individual behaviour is important, social level analysis provides a broader framework for understanding residential energy use. As a result models such as cultural model of household energy consumption [35] and Value-belief-norm theory applied to residential energy use [32] have been developed. The importance of looking at residential demand response from social science perspective has recently been re-emphasized by Yolande Strengers [36].

3. Residential demand response pricing strategies

Programs that investigate the impact of price on electricity demand usually feature time-of-use (TOU) tariffs. TOU tariffs charge different prices for electricity used within defined time periods. These prices are fixed for the blocks of time within which they apply as illustrated in Fig. 1a. The price per kWh of electricity used at peak hours is higher than electricity used during off-peak hours.

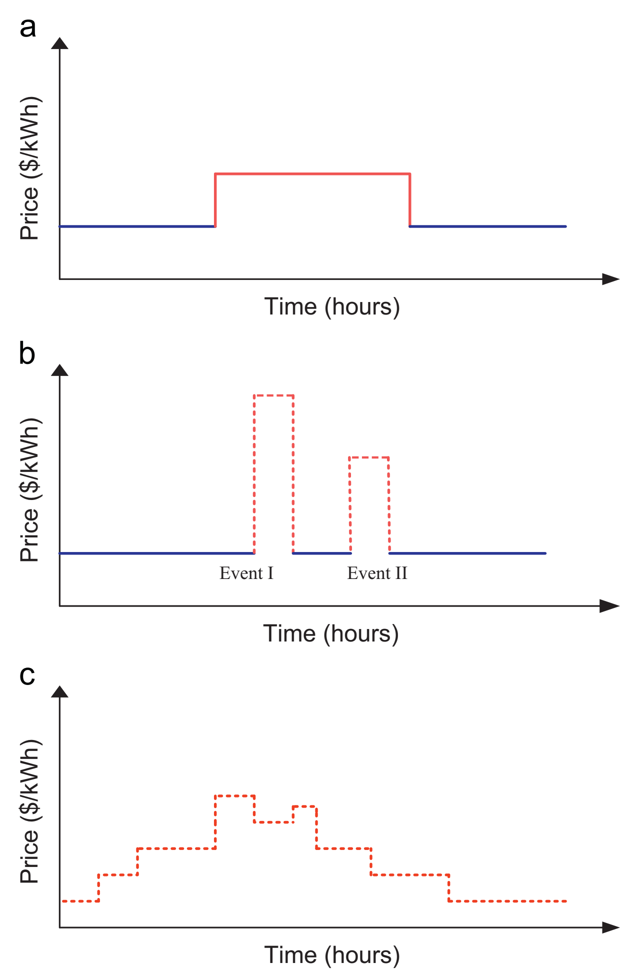


Fig. 1. Schematic sketches of the types of time varying price structure. (a) Time-of-use, (b) Critical-peak-pricing) and (c) Real-time-pricing.

Due to the static nature of these tariffs (i.e. fixed price at specific time range), some studies have investigated the impact of dynamic tariffs, such as critical peak pricing (CPP) tariffs and real-time-pricing (RTP) tariffs. CPP tariffs have higher charges for electricity used during the periods that are designated as critical by the utility. This tariff structure is similar to the TOU rates except that the times and the prices are not fixed as illustrated in Fig. 1b. The dotted lines indicate that prices are not fixed and could move in both vertical and horizontal directions depending on the system condition. There is a customer friendly approach to dynamic tariffs known as peak time rebate (PTR). It is dispatched the same way as CPP however; customers remain on their existing tariffs but receive rebate payments if they reduce their consumption during peak load events. The rebate payment is usually based on the reduced consumption from a calculated baseline (based on an event day). Real time pricing (RTP) tariffs on the other hand vary continuously based on wholesale price or regional demand as shown in Fig. 1c.

Demand response programs are reported in various ways, usually as the effect of the program in reducing peak demand, which is the goal of most programs. This effect is usually expressed as a percentage of the peak load or as kilowatt reduction per customer. In addition to the above, dynamic pricing programs often include customer price elasticity. The next section presents results of some studies conducted in different countries.

3.1. Time of use (TOU) rates

The U.S. Federal Energy Administration initiated 14 experiments in the 1970 and 1980s to gain knowledge about how customers would change their electricity usage in response to TOU tariffs. Some years after the experiments, Caves and Christensen initiated a study to investigate whether consistency could be found across the experiments when differences in the experimental characteristics were controlled [37]. They reviewed several experiments and selected five with sufficient high quality that could be used to pool the data. The selected experiments were from Carolina Power and Light, Connecticut Light and Power, Los Angeles Department of Water and Power, Southern California Edison, Wisconsin Public Service. Their pooled model yielded estimates of elasticity of substitution for any combination of appliance ownership, and house type, household size and climate. For summer, they found the elasticity of substitution to be 0.14 for a typical customer and 0.07 for customers without major appliances (such as air conditioners), while the elasticity for a customer with all the major appliances was found to be 0.21. For winter, the results were 0.10 for a typical customer, 0.06 for a customer without major appliance and 0.17 for customers with all major appliances.

A more recent large-scale pricing experiment of this nature in the U.S. was the California State Wide Pricing Pilot, conducted to test the impact of several pricing structures, including TOU price on peak demand [38]. A total of 2500 customers were involved in the experiments that ran from July 2003 to December 2004. This experiment found an average demand reduction of 13% for low-demand customers (mainly residential customers with demand less than 20 kW). The estimated price elasticity of substitution varied from 0.04 to 0.13 for a peak to off-peak price ratio of 3 to 6 [38].

In Germany, tariff experiments with TOU prices for residential customers took place in the 1970s and 1980s. Examples of places where the experiments were conducted are Freiburg and the German State of Saarland [39]. In Freiburg, the TOU tariff was tested for 450 households over a duration of about 1 year. The tariff had three different prices on workdays and only two prices at the weekend. The peak time price was about two and half times higher than the off-peak price. In between, there was a shoulder peak price of 1.5 times the off-peak price. The study found a reduction in peak demand of 3% and reduction in electricity consumption of 8%. The state of Saarland experiment which involved a much larger population (1500 households) found a peak demand reduction of 10%.

In Switzerland, Filippini examined the impact of TOU pricing on residential electricity demand in the mid 1990s. For this purpose, a model of two log-linear stochastic equations for peak and off-peak electricity consumption were estimated from the aggregate of 4 year electricity prices and demand data covering 40 cities [28]. The study found Swiss households to be highly responsive to electricity price changes. Short-run price elasticities of −0.60 during the peak period and −0.79 during the off-peak period were estimated in the study.

King and Chatterjee reviewed price elasticities estimated in 52 experiment in the residential and small commercial sector (in the US and international) conducted between 1980 and 2003 and found average own-price elasticity of −0.30. Majority of the experiments have their elasticity lying between −0.10 and −0.40 with two outliers in the range of −0.70 and −0.80.

Filippini carried out a similar study in Indian households, but this time using disaggregated household level survey data [29]. The study estimated household electricity demand elasticity with respect to price (and also income) for each of the three seasons in India (winter, monsoon and summer). The study estimated price elasticity of –0.42 for winter, −0.51 for summer and −0.29 for the monsoon season.

Table 1 gives a summary of TOU studies reviewed in this study. These results across the three continents (Asia, Europe and America) indicate that residential customers do respond to a time dependent electricity tariff, but the extent of their response varies in each of the studies. This may be expected due to the differences in the study methodology and also the share of energy costs of the total household budget in the study area. The elasticities estimated from computational methods are much higher than those estimated from measured and survey data. For example, there is a large difference between the computed results for the Swiss and Indian households by Filippini compared to the other studies. Also, if the costs of energy are marginal to households, they may be insensitive to price signals [15]. The magnitude of demand response with respect to price when expressed as a percentage of peak loads has been found to be higher for low-income households compared to high income households [40].

3.2. Dynamic pricing

Residential dynamic tariff programs include real-time pricing (RTP) and critical-peak pricing (CPP). An example of a residential RTP tariff is that of Commonwealth Edison of Chicago in the USA. The program uses low cost technology (internet, text message and automated phone call) to inform participants about the prices of electricity over the day. These prices are based on the actual price of electricity in the wholesale market. Customers are told a day in advance of hourly prices via the internet [41]. They receive a special notice or “pricing alert” via text messaging and automated phone call when prices exceed a certain threshold (0.14 U.S. cents/kWh in 2012). A price elasticity of -0.049 was determined from the program experiment conducted in 2005 [14].

Another RTP experiment is the GridWise Olympic Peninsula Project [42] that tested the impact of RTP on electricity usage for 112 households in Olympia, Washington. Households were equipped with smart technologies (smart communication devices and smart appliances) that could be programmed to respond to TOU, CPP, and RTP prices that change as frequently as every 5 min. The experiment lasted for about a year, from March 2006 to March

Table 1
A summary of TOU studies reviewed.

Region	Elasticity type	Estimated elasticity	Comment	Year of experiment	Source
US (California, Connecticut, Wisconsin)	Substitution	0.14/10 winter/summer typical customer 0.07/0.06 Winter/Summer customers without major appliances 0.21/0.17 winter/summer major appliances customers	Pooled result from five residential TOU	1977–1980	Cave and Christensen [37]
US (California)	substitution	0.04–0.13	13% Peak reduction	2003–2004	Charles River Associates [38]
Germany (Freiburg)			3% Peak reduction 8% consumption reduction	1970 and 1980s	Barbara Schlomann [39]
Germany (Saarland)			Peak reduction 10%	1970 and 1980s	Barbara Schlomann [39]
Switzerland (40 cities)	Own-price	−0.60 Peak hours-0.79 off-peak hours	Modelling results using aggregated data	1990	Filippini [28]
India	Own-price	−0.42 (Winter) −0.51 (summer) −0.29 (monsoon)	Modelling results using disaggregated household level data	2002	Filippini[29]
US and international	Own-price	−0.30	Average of 54 international studies		King and Chatterjee [40]

Table 2
A Summary of dynamic pricing studies demand response program.

Region	Elasticity type	Estimated elasticity	Comment	Year of experiment	Source
US Chicago	Own-price	−0.049	Residential RTP	2005	ComEd [42]
US (Washington)			15% contribution to peak demand reduction	2007	Hammerstrom[43]
France	Own-price	−0.79 peak -0.18 off-peak	CPP; Average of 1 kW per household peak reduction	1996	Aubin [45]

2007. It was designed to mimic the expected future of the electric power industry where distributed generation is expected to be used to meet a significant proportion of the electricity demand. One of the objectives of the project was to gain an understanding of how the resources perform individual and when interacting near real-time to meet common grid management objectives. The distributed systems used in the experiment were five 40-HP water pumps distributed between two municipal water pumping stations representing a name plate total of 150 kW, two diesel generators of capacity 175 and 600 kW. The residential demand response was used together with these distributed generation resources to respond to stresses on a virtual distribution feeder. The contribution of each resource was monitored online using an interface that shows how much of it has been dispatched and how much is available. The average contribution of the residential demand response to system peak demand reduction was determined to be about 15% [42].

The critical peak pricing tariff is an example of a commonly used tariff to reduce peak demand in the residential sector. In France, the Electricity de France (EDF) introduced critical peak price tariffs for its residential consumers in 1996. Prior to this introduction, they conducted an experiment with the so-called *tempo tariff*. With this scheme, the year was divided into 22 red, 43 white and 300 blue days, and each day had a peak and an off-peak period. The red day charges were the highest prices and had the largest peak/off-peak price ratio, while the blue day charges were the lowest prices with the smallest ratio. Customers were informed of the next day's colour at the end of each previous day (usually at 8 p.m.) through a "smart meter" ("*Le compteur électronique*"). The prices corresponding to the colours were fixed and known to the customers, but the colour itself was unknown until the evening before the pricing came into effect.

The program participants from the residential sector totalled about 350,000. The tempo tariff led to a reduction in electricity consumption of 15% on white days and 45% on red days, representing an average reduction of 1 kW per customer [43]. An unusually high price elasticity of −0.79 was estimated for the peak demand and −0.18 for off-peak demand [44]. While the Tempo tariff has been successful, less than 20% of electricity customers in France have chosen this tariff option. It is important to note that the Tempo tariff was designed specifically for the situation where EDF is a monopolistic generator and retail supplier of electricity.

Several experiments have been conducted to test the impact of electricity prices on demand. They have taken place in many places across the globe. More information about these kinds of studies can be found in the references [14, 30, 45, 46]. The studies vary significantly in method, test sample sizes and results. Table 2 gives a summary of dynamic pricing studies reviewed. It is worth mentioning that price elasticity determined in the Commonwealth Edison of Chicago RTP study is very low compared to that of other studies that use TOU and CPP tariffs. Though very difficult to make conclusion based on the limited number RTP studies that are out there, one can only say that, perhaps consumers can better identify with TOU and CPP and their response is better.

4. Some issues about price-based demand response

4.1. Price unresponsiveness

While the results of most studies show that residential customers do respond to a time-varying electricity price, a detailed analysis by Reise and White indicates that a significant proportion of households do not respond to price [15]. Using extensive data

for a representative sample of 1300 Californian households, the results of their model showed a strikingly skewed distribution of household electricity price elasticities in the population, with a small fraction of households accounting for most of the aggregated −0.39 price elasticity found by the study. Price elasticities determined for the households ranged from −2.0 to 0. Where a household is located in the elasticity distribution is related to household income and amount of electricity the household consumes. The elasticity decreases as household's income increases. Elasticity of the lowest income (annual income less than $US 18,000) households was almost 50% higher than that of the highest income (annual income greater than $US 60,000) households). A significant fraction of households (44%) did not show any price responsiveness. Households with major appliances, like space heating and air conditioners, responded the most. [15]. Based on these findings, Reise and White concluded that there are two main groups of households: those that use electricity for space heating or air conditioning and exhibit some electricity price responsiveness and those that do not use electricity for either of the purposes stated above and exhibit near zero elasticity. Another conclusion that can be drawn from the study is that households demand responsiveness to price decreases as household income increases.

4.2. Equity issues

There have been mixed opinions about the impact of price on low socio-economic households. One opinion has it that high prices would disproportionately affect low income households who do not have the capacity to take action to avoid paying high peak prices [47]. If low income households would be able to reduce their demand, they would do so at the expense of their comfort and wellbeing, as well as convenience[48]. This could be true because low-income households typically use less energy than the average consumer; as a result their ability to conserve energy is reduced [49]. Also, when confronted with an increase in energy costs, lower-income families tend to make “lifestyle cutbacks” [48]. The evidence of this is the increase in “food insecurity” among the elderly households during periods associated with high heating and cooling demand when they spend a significant proportion of their income on energy (see the discussions in [47]). Another example is in Queensland, Australia, where the number of consumers contacting the Ombudsman over “account payment difficulties” almost quadrupled to 1103 in 2008–2009 as electricity prices increased [50]. Based on the equity concern, three approaches to achieving cost-effective demand response have been suggested to take care of vulnerable households: the use of energy efficiency measures; a voluntary approach to dynamic pricing, including time of use pricing and peak time rebate [47].

On the other hand, if load profiles of low income households are such that demand could be shifted to off-peak periods, then they could benefit from demand response. The most recent analysis by Ahmad Faruqui of the Brattle Group, using data from an urban utility shows that about 80% of low-income customers would actually gain from dynamic pricing. With a modest amount of demand response the percentage increases to about 92%.

4.3. Smart metering cost

Another issue that often comes up in the discussion of demand response and Advanced Metering Infrastructure (AMI) or Smarter Meters is whether customer response to time-varying pricing would be sufficient to offset the investment and maintenance costs of AMI. This is seen as one of the barriers to the rapid up-take of demand response in the residential sectors in Europe [51]. Even if it is assumed that investment in this smart technology has the potential to lower prices in the long-run, most utilities will not choose to or agree to absorb the additional costs in the short-run. Analysis done by Faruqui and Sergici shows that at least part of the cost would have to be *borne* by the residential customers [14], possibly in the form of monthly fixed charges. Higher monthly fixed charges may have a more adverse impact on lower income customers where the fixed charges represent a higher percentage of the total monthly bill [14].

5. Conclusions

From the literature on demand response, the fundamental assumption has been that there is no better signal than price and that socially optimum behaviour can be brought about with “high” prices. Despite the growing interest in price-response, experience with such programs shows mixed results. Dynamic pricing is in the category of price response programs that has garnered the greatest attention in recent times. While customers have been found to respond to price on an aggregate level, a more detailed study shows a surprisingly high fraction of households that do not respond to price. This may be due to different reasons. Some ‘rich’ households may not care about the price of energy as it is only a tiny fraction of their available budget. Some households may lack the competence to respond to the price signal (e.g. may not understand the pricing system or do not learn due to missing immediate feedback). Some households may either not have the capacity or decision options to respond.

The above results need to be considered in the design of residential demand response programs. Researchers in demand response need to recognize that prices alone will not necessarily create the conditions needed to achieve effective peak demand management that could be reliably deployed to reduce the need to build more generation and transmission infrastructure. Social and psychological researches have shown that people's behaviour can be explained by a combination of different factors (e.g. norm, beliefs, values etc.). For example, people who place much value on the environment will be more likely to respond to environmental information than they would do with price information. The benefits of demand response to consumers in all sectors include lower peak price, market discipline, and reliable electrical service and possibly lower environmental emissions. Better explanation of all these benefits to the consumer is perhaps necessary to achieve effective demand response in the residential sector.

An experimental test conducted by the authors [52] a couple of years ago on residential customers using price, environment, and security as response signals showed a promising result for security and environment to be used as response signals; with the security signal having the same effect on demand as price. We therefore suggest the range of signals for residential demand response leave customers with room to act on voluntary bases, based on their capacity to respond. We further suggest that demand response engineering should use a hybrid approach employing knowledge from social psychology and economic behaviour models.

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